Intelligent Aerodynamic/Propulsion Flight Control For Flight Safety: A Nonlinear Adaptive Approach

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Abstract

This paper presents an intelligent fault tolerant flight control system that blends aerodynamic and propulsion actuation for safe flight operation in the presence of actuator failures. Fault tolerance is obtained by a nonlinear adaptive control strategy based on on-line learning neural networks and actuator reallocation scheme. The adaptive control block incorporates a recently developed technique for adaptation in the presence of actuator saturation, rate limits and failure. The proposed integrated aerodynamic/propulsion flight control system is evaluated in a nonlinear flight simulation environment.

1 Introduction

Actuator failure during flight poses a significant flight safety concern. Landing an aircraft in the presence of actuator failures is extremely challenging even to the most experienced pilot. Recent accidents have been caused by the loss of a single actuator, or the loss of all hydraulic controls.[1]

Conventional flight control systems require extensive gain scheduling for a large number of operating points within the aircraft flight envelope. When such a controller must be extended to account for actuator failures, a complete redesign is required for each anticipated failure case at all the gain scheduled operation points. Many types of failures can be envisioned, including but not limited to hardovers, loss of actuator effectiveness, and free-floating actuators. This leads to a very large scheduling table, making it difficult from design and real time implementation standpoints. In addition, a truly fault tolerant control system must also be able to accommodate non-anticipated failures.

Neural Network (NN) based adaptive flight control, within the setting of feedback inversion control, has been shown to require no gain scheduling and is only minimally model dependent .[2-4] Consequently, these flight control systems can accommodate a multitude of unknown actuator failures, which act as disturbances on the aircraft. Hence, they provide an attractive candidate flight control architecture to ensure flight safety in the presence of unknown actuator failures. However, its application to civil transports requires special attention due to the fact that redundant actuation is only possible through low bandwidth and low authority mechanisms that are usually not intended to be active as a part of the primary flight control system.

The objective of this work is to design an intelligent nonlinear adaptive control architecture that can respond to faults in the system, by utilizing redundancy in the controls. Refs. 3 and 4 demonstrated that such a system could effectively control an aircraft with major actuator failures. Refs. 5 and 6 use a non-adaptive gain scheduled control design for pure propulsion control to provide stability augmentation for a large transport aircraft without any aerodynamic actuation. Ref. 7 demonstrates that similar performance is attainable by employing an adaptive controller without gain scheduling, using a linear model at a single flight condition for feedback inversion. However, those results were limited to examining small command inputs so that position and rate saturation are avoided, to guarantee stability and proper NN adaptation. In this paper, the problem of continuous control in the presence of both partial and complete loss of a single or multiple actuators is addressed, while utilizing all the remaining control effectors. A recently developed pseudo-control hedging (PCH) methodology[4,8,9] is employed to protect the system from the adverse affects of incorrect adaptation in the presence of slow actuation, actuator saturation and actuator failure.

2 Intelligent Flight Control System Components

The proposed flight control system is constructed as a Model Reference Adaptive Control (MRAC) scheme, with appropriate modifications required to blend aerodynamic and propulsion control, while operating with possibly saturated or failed actuators. Figure 1 presents the conceptual layout of the system, which incorporates an approximate dynamic inversion block, a linear compensator and an on-line adaptive NN. The system is driven by the outputs of a reference model, which has a non-standard input from the PCH element introduced for proper adaptation in the case of actuator saturation or failure.

The main advantage of the proposed control setup is in its minimal dependence on a specific aircraft model. The adaptive NN is used to compensate for a wide range of modeling (inversion) errors, which may include the effect of failed actuators. The compensator design is straightforward and relies mainly on linear control theory. The NN adaptation rule results from nonlinear stability analysis, which ensures that the error signals and network weights are bounded. In this section, the various elements of this controller setup are discussed.

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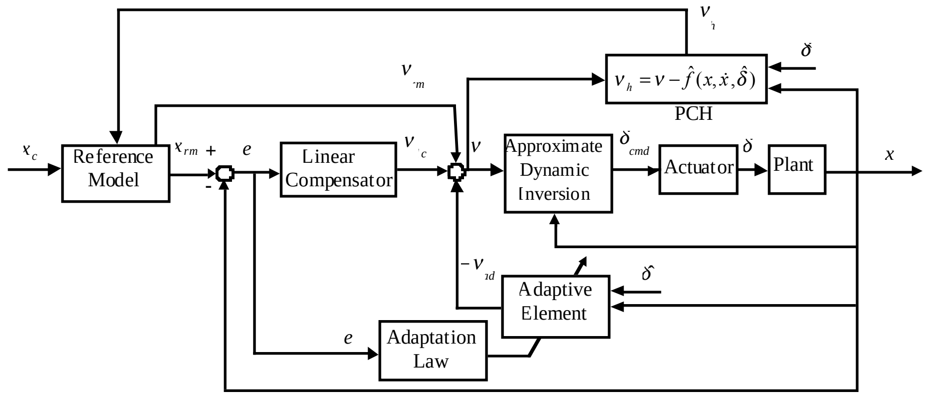

Figure 1. Model Reference Adaptive Control Setup, Including Approximate Dynamic Inversion and Pseudo-Control Hedging Compensation.

2.1 Approximate System Linearization

One of the common methods for controlling nonlinear dynamical systems is based on approximate feedback linearization.[10] The form that is employed in each control channel depends on the relative degree of the controlled variable. To simplify our discussion, we assume that the system has full relative degree, where each controlled variable (element of the state vector) has a relative degree of two

$$\ddot{x} = f(x,\dot{x},\delta) \tag{1}$$

In the case of aircraft, typically $x,\delta \in \Re^3$, where the elements of x correspond to the roll, pitch and yaw attitude angles. A variant of this form arises in which angular rate is controlled. Here, the equation of motion for that degree of freedom is expressed in first order form[3]. A pseudo-control ν is defined such that the dynamic relation between it and the system state is linear

$$\ddot{x} = \nu \tag{2}$$

where

$$\nu = f(x,\dot{x},\delta) \tag{3}$$

Ideally, the actual controls (δ) are obtained by inverting Eq. (3). Since the function $f(x,\dot{x},\delta)$ is not known exactly, an approximation is defined

$$\nu = f(x,\dot{x},\delta) \tag{4}$$

which results in

$$\ddot{x} = \nu + \Delta(x,\dot{x},\delta) \tag{5}$$

where the modeling error is represented by

$$\Delta(x,\dot{x},\delta) = f(x,\dot{x},\delta) - f(x,\dot{x},\delta) \tag{6}$$

The approximation, f, is chosen such that an inverse with respect to δ is computable. Consequently, the actuator command is constructed as

$$\delta_{cmd} = \hat{f}^{-1}(x,\dot{x},\nu) \tag{7}$$

Approximate dynamic inversion produces a model inversion error that will be adaptively compensated using an on-line neural network. As shown in Figure 1, the total pseudo-control signal is constructed of three components

$$\nu = \nu_{rm} + \nu_{lc} - \nu_{ad} \tag{8}$$

where ν_{rm} is the pseudo-control component generated by the reference model, ν_{lc} is the output of the linear compensator, and ν_{ad} is generated by the adaptive element introduced to compensate for the model inversion error. In the case of perfect actuation $(\delta = \delta_{cmd})$, the commanded pseudo-control signal generated by the reference model equals $\ddot{x}_{rm}$, the acceleration of the reference model state.

2.2 Linear Compensator Design

A linear compensator is designed for each degree of freedom assuming perfect inversion $(\hat{f} = f)$. If the controlled variable has relative degree two (as illustrated in the preceding section), the state tracking error dynamics associated with the linearized plant have two poles at the origin. The linear compensator is designed so that the error dynamics are stabilized. This is most often achieved using standard proportional-derivative (PD) controllers, although additional integral action can be incorporated to improve steady state performance. In general, the linear compensator can be designed using any technique as long as the linearized closed loop system is stable.

For the second order system, PD compensation is expressed by

$$\nu_{lc} = [K_P \quad K_D]e \tag{9}$$

where the state tracking error is defined by

$$e = \begin{bmatrix} x_{rm} - x \\ \dot{x}_{rm} - \dot{x} \end{bmatrix} \tag{10}$$

The compensator gain matrices $K_P, K_D \in \Re^{3\times 3}$ are chosen so that the tracking error dynamics given by

$$\dot{e} = Ae + B(\nu_{ad} - \Delta) \tag{11}$$

$$A = \begin{bmatrix} 0 & I \\ -K_P & -K_D \end{bmatrix}, \qquad B = \begin{bmatrix} 0 \\ I \end{bmatrix} \tag{12}$$

are stable, i.e., the eigenvalues of A are prescribed. It is evident from Eq. (11) that the role of the adaptive component, ν_{ad}, is to cancel Δ.

Eqs. (6-8) imply that the model inversion error Δ is a function of the pseudo-control ν and consequently of the NN output ν_{ad}. To guarantee existence and uniqueness of a solution for ν_{ad} that produces any (unknown) Δ, it is assumed that the map $\nu_{ad} \mapsto \Delta$ is a contraction. It can be shown that this is equivalent to the following two requirements on $\hat{f}$:

$$\operatorname{sign}\left(\frac{\partial \hat{f}}{\partial \delta}\right) = \operatorname{sign}\left(\frac{\partial f}{\partial \delta}\right) \tag{13}$$

$$\left|\frac{\partial \hat{f}}{\partial \delta}\right| > \left|\frac{\partial f}{\partial \delta}\right| / 2 > 0 \tag{14}$$

The linearized closed loop system is driven by the output of an at least 2nd order reference model. The reference model is hedged in the presence of saturation or failure using the pseudo-control hedging methodology, presented next.

2.3 Pseudo-Control Hedging

PCH introduces a modification to previous work on NN based model reference adaptive flight control. It is used to address NN adaptation difficulties arising from various actuation anomalies, including actuator position and/or rate saturation, discrete (magnitude quantized) control, actuator dynamics, and partial or complete actuator failures.

NN training difficulties occur when unmodeled actuator characteristics are encountered. For example, unless an adaptive process is specifically protected against it, saturations that result from failed operation quickly lead to NN wind-up. The main idea behind the PCH methodology is to limit or hedge the reference model of a MRAC architecture to prevent the adaptive element from attempting to adapt to these characteristics, when they are present, while not affecting the NN adaptation to other sources of inversion error, for which compensation is possible.

Conceptually, PCH "moves the reference model backwards" by an estimate of the amount the controlled system did not move due selected actuator characteristic (such a position and rate limits, time delays, etc). In effect, the reference model, which produces the commanded pseudo-control, is limited or hedged according to the difference between the commanded and actually achieved pseudo-control. PCH prevents the NN from adapting erroneously to actuator saturation or failure by interpreting their effect as model tracking errors. With PCH, the NN is trained correctly using only achievable pseudo-control signals. The same concept holds when the actual pseudo-control action is due to a different control logic (element) and not the MRAC that incorporates the training NN, i.e., training while not in control.

To briefly review the PCH concept, consider the case of full model inversion, in which the plant dynamics is as in Eq. (1). The pseudo-control signal defined in Eq. (4) represents, in this simplified presentation, the desired acceleration, while the actuator commands are given by Eq. (7). The dynamic inversion element is designed while neglecting the actuator model. Hence, this actuator command (δ_{cmd}) will not equal the actual actuator position (δ) due to its dynamics, saturation and/or failure. The pseudo-control hedge signal ν_h is defined as the difference between the commanded pseudo-control input and the actually achieved pseudo-control, which is non-zero only when the commanded actuator position is different from its actual value. To compute this difference, a measurement or an estimate of the actuator position $(\hat{\delta})$ is required. This estimate is then used to compute the pseudo-control hedge as

$$\nu_h = \hat{f}(x, \dot{x}, \delta_{cmd}) - \hat{f}(x, \dot{x}, \hat{\delta}) = \nu - \hat{f}(x, \dot{x}, \hat{\delta}) \tag{15}$$

The PCH signal is next introduced as an additional input into the reference model, forcing it to "move back". If the reference model update *without PCH* was of the form

$$\ddot{x}_{rm} = f_{rm}(x_{rm}, \dot{x}_{rm}, x_c) \tag{16}$$

where x_c is the external command signal, then the reference model update *with PCH* is set to

$$\ddot{x}_{rm} = f_{rm}(x_{rm}, \dot{x}_{rm}, x_c) - \nu_h \tag{17}$$

The instantaneous pseudo-control output of the reference model that is used as an input to the linearized plant model is not changed by the use of PCH and remains

$$\nu_{rm} = f_{rm}(x_{rm}, \dot{x}_{rm}, x_c) \tag{18}$$

Hence, the effect of the PCH signal on the pseudo-control is introduced only through the reference model dynamics. This results from the stability analysis of NN based adaptive control with PCH, detailed in Ref. 9.

2.4 Neural Network for Inversion Error Compensation

In this study, a nonlinear single hidden layer (SHL) NN is used to compensate for the inversion error. The SHL NN was chosen because of its universal approximation property.[11,12]

For an input vector $\bar{x}$, which is constructed of the measured states, the reference model outputs and the pseudo-control signal, the output of the SHL NN is given by

$$\nu_{ad} = W^T \sigma\left(V^T \bar{x}\right) \tag{19}$$

where V and W are the input and output weighting matrices, respectively, and σ is a sigmoid activation function. Although ideal weighting matrices are unknown and usually cannot be computed, they can be adapted in real time using the following NN weights training rules[8,9]:

$$\dot{W} = -\left[\left(\sigma - \sigma' V^T \bar{x}\right)\eta + \kappa \|e\| W\right]\Gamma_W \tag{20}$$

$$\dot{V} = -\Gamma_V \left[\bar{x}\eta W^T \sigma' + \kappa \|e\| V\right] \tag{21}$$

where Γ_W and Γ_V are the positive definite learning rate matrices, σ' is the partial derivative of the sigmoids σ with respect to the NN inputs $\bar{x}$, and κ is the e-modification parameter. η is defined by

$$\eta = e^T PB \tag{22}$$

Here, $P \succ 0$ is a positive definite solution of the Lyapunov equation

$$A^T P + PA + Q = 0 \tag{23}$$

for any positive definite $Q \succ 0$. A and B in the above equations are the tracking error dynamics matrices defined in Eq. (12).

3 Actuator Failure Accommodation

A completely failed actuator may introduce no actuation at all (in the free floating surface case) or cause a significant disturbance input (in the frozen case, especially during hardovers.) To accommodate these failures, secondary actuation systems must be used to maintain control and at least minimal performance of the aircraft in its flight safety critical tasks.

To avoid scheduling and repeated designs for different failures, it is desirable that the design and operation of these secondary actuation systems do not depend specifically on the exact nature of the primary actuator failure. An adaptive control scheme, which can address the unknown actuator inputs as modeling errors, is most appropriate for that task. Examining the model error Eq. (6) reveals that any failure that can be modeled as a (not necessarily known) function of the system states can be addressed using the adaptive control scheme presented in the previous section. This failure characterization is not overly restrictive, because such functional dependence can represent most of the commonly encountered actuator failures, such as position frozen actuators, hardovers, free floating aerodynamic surfaces, and many more. Hence, the NN based adaptive secondary actuation systems are designed while disregarding the possible failures of the primary actuators. The on-line tuned NN of these channels will adapt to the failure driven inputs, interpreted as modeling errors, and compensate for their effect.

Thus, following a failure, the actuation strategy is modified to apply secondary control effectors on a failed channel. It is assumed that the presence of the actuator failure is known from other information sources (external failure detection algorithms or on-line monitoring), however no knowledge of the failure type or "size" is required. The knowledge that a failure occurred is used only for engaging the secondary control channel. Often, the secondary actuators are less effective for the primary control task. The lower authority of the secondary actuation systems will necessarily lead to a lower performance control design, reflected in the reference model and linear compensator characteristics. In addition, these actuators may saturate or not produce the required control effort. Hence, the PCH methodology is central for efficient application of nonlinear adaptive control in these secondary channels.

Based on this concept, a chain of alternative actuation modes can be constructed to accommodate a multitude of actuator failures. These alternative control modes will remain in stand-by status and will be engaged only after a failure has occurred. The only requirement here is the knowledge that a particular actuation system has failed. As an example, a chain of alternative aerodynamic and propulsion actuations can be applied for continuous pitch rate control of an aircraft. In normal un-failed mode, elevators control pitch rate. If elevator failure is encountered, symmetric ailerons can be introduced for this task, while compromising performance. However, if the elevator failure was caused by a loss in the hydraulic power, there is a chance that the ailerons are also inoperative. In this event, the propulsion system can be engaged to maintain at least partial pitch control for safe (stable) flight, with a compromise in speed control normally obtained by a propulsion based control logic. Similar control re-allocation logic can also be constructed for the lateral stability control channels of the aircraft.

An important feature of the proposed control setup and the re-allocation scheme is that the primary control channels can be synthesized using any control design technique. This implies that the proposed concept can be added to an existing certified flight control system, thus further enhancing its flight safety characteristics. No modifications are required to the existing control channels logic or architecture. The only requirement is for an actuator fault detection algorithm and a switching logic between the various channels. The latter aspect of this flight safety system is addressed in a follow-up paper.[13]

4 Numerical Evaluation

Performance of the proposed adaptive system for actuator failure accommodation is tested on a numerical model of the Boeing 747 aircraft.[14] The aircraft model is constructed of 6DOF nonlinear kinematics, linearized aerodynamics and propulsion modules, and first-order, rate and position limited actuators. In this example, control of the longitudinal channels will be demonstrated.

The primary longitudinal control channels are pitch rate control using the elevator and forward flight speed control using thrust, i.e., throttling. Classical linear controllers are used in these two primary control channels.

Of the two, pitch rate control is considered critical, while speed control can be abandoned, if necessary, in the event of an elevator failure. After elevator failure, secondary pitch rate control is achieved first through symmetric aileron actuation. If the ailerons also fail or saturate due to their limited pitch rate authority, speed control is abandoned and symmetric thrust is engaged for pitch rate control.

The two primary channels are non-adaptive PI controllers to track reference models with natural frequencies and damping coefficients shown in Table 1. The secondary NN based control channels have 6 hidden neurons each. The approximate dynamics $(\hat{f})$ are assumed to be linear functions of the actuator commands, where the constant gains are an estimate of the respective actuators' effectiveness. The relative degree of the symmetric ailerons to pitch rate transmission is one, and the linear controller is a standard PI compensator. The relatively low bandwidth of the throttle control is included in the design of the propulsion to pitch rate secondary channel. This relative degree two channel is controlled by a PD controller. The dynamic characteristics of the secondary channels are also shown in Table 1.

Table 1. Controller parameters.

Mode	Actuator	ω_n	ζ
Pitch Rate, primary	Elevator	3.0	0.70
Pitch Rate, secondary	Sym. Ailerons	3.0	0.70
Pitch Rate, secondary	Engines	2.0	0.70
Speed, primary	Engines	0.3	0.70

The aircraft response to a square wave pitch rate command is shown in Figure 2. The corresponding actuator positions are shown in Figure 3. At t=30 seconds, the elevator is failed (frozen). In the time interval of 30 to 60 seconds, symmetric aileron control is engaged for pitch rate control, until it is also failed at t=60 seconds. For the remainder of the simulation, pitch control is achieved with thrust only, while compromising speed control. Figure 3 shows the actuator command signals. The engines briefly saturate on their lower limit twice, but this limited duration saturation has no significant effect on performance.

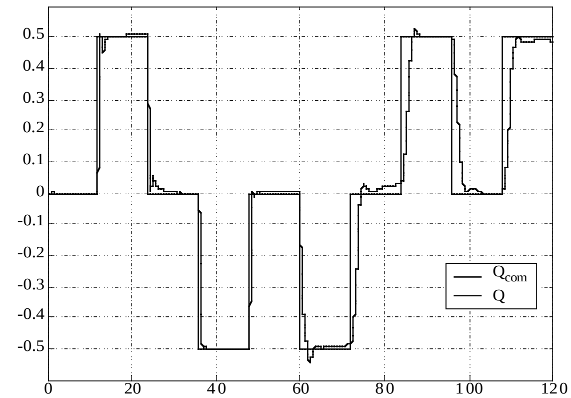

Figure 2. Pitch response during failures.

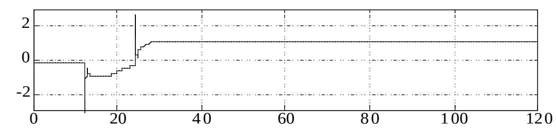

Figure 3. Actuators' positions.

The elevator and aileron control loops are only engaged for the first and second 30-second periods, respectively, while the engine is being continuously throttled by the velocity control loop for the first 60 seconds and the pitch control loop for the remainder of the simulation. The forward velocity perturbation, u , is shown in Figure 4. While the primary thrust channel is engaged, it holds the speed almost constant while the aircraft changes its pitch attitude. Obviously, after speed control is discontinued in favor of the thrust to pitch rate channel, flight speed variations of up to 40ft/sec can be observed.

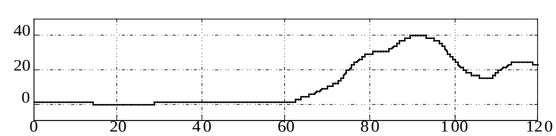

Figure 4. Speed perturbation from initial trim value.

Figure 5 shows the successful identification of the model inversion error by the NN. The NN output of the symmetric aileron channel is compared here to the computed inversion error. The aileron control loop learns the appropriate inversion error for the time period when it is in control (t=30-60 seconds), and also the period when it is not.

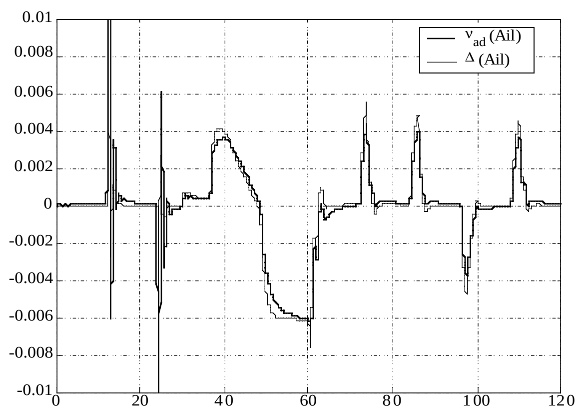

Figure 5. NN output and inversion error for the aileron channel.

5 Summary

This paper presents an adaptive, NN based flight control design methodology for actuator failure accommodation. Safe flight is maintained by incorporating stand-by control channels, which utilize secondary actuators to continuously maintain satisfactory or at least stable operation. The known actuator failures of unknown type and magnitude are treated as modeling errors and compensated by the adaptive NN based element of the secondary control channel. Each of these secondary control channels is designed for the primary control task, while accounting for the dynamic characteristics of the channel, the possible degraded authority of the secondary actuator and the limited achievable performance. Since the design of the secondary channels does not depend on the architecture of the nominal case controller, the proposed methodology is ideal for safety retrofit of any flight control system.

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